A Software Sensor for Motorcycle Suspension Stroke

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***Abstract*—Electronic instrumentation and sensors are playing a relevant role in preventing and detecting road accidents, and improving the overall driving experience. Consequently fault detection on vehicle instrumentation and sensors also emerged as a main topic for its direct impact on cost and road safety. As solution, the employment of the analytical redundancy of measurement information is particularly suitable and/or necessary. This paper is about the estimation of suspension stroke exploiting the analytical redundancy among the measurement signals provided by a typically adopted instrumentation set. A software sensor for the rear suspension is designed according to a systematic approach, which is focused on recurrent Artificial Neural Networks able to predict the dynamic behavior of the vehicle. Experimental results show the rear suspension elongation can be correctly estimated. They disclose the possibility of setting-up an effective Instrument Fault Detection and Isolation scheme based on the real-time adoption of the proposed software sensor in order to improve the system reliability.**

Keywords — software sensor, sensor validation, artificial neural networks, instrument fault detection

I. INTRODUCTION

Soft Sensors are generally meant the process of estimation of any system or process variable by using mathematical models, substituting some physical sensors and using data acquired from some other available ones [1]. Soft Sensors have been proposed to solve problems such as measuring system back-up, what-if analysis, real-time prediction for process control, sensor validation and fault diagnosis strategies. They are currently profitably used in closed-loop inferential and/or adaptive control schemes [2].

Since the direct implications on cost-saving and safety, the smart sensing has become an interesting topic also for the field of two-wheeled vehicles, where the spread of electronic control systems is still in its infancy (for example, today, only a few commercial motorbikes are equipped with ABS control systems). As an example, the tilt-angle estimation is proposed in [3] via two different algorithms and methods based on a set of gyroscopes and a longitudinal speed sensor. Generally speaking, soft sensors based on analytical redundancy have been investigated in order to improve control algorithms aiming to both riding comfort [4] and road-holding [5]. A typical approach is the adoption of Kalman Filters: in [6] KF were proposed as real-time acceleration-based estimators of the elongation velocity and damping force for single semi-active shock-absorber in order to improve noise filtering and/or implement virtual sensor (typically one accelerometer on the wheel side could replace the suspension stroke sensor and/or the cell load with acceptable performance).

Since measurement information about suspension dynamics (in terms of elongation and/or velocity) is necessary to implement whichever strategies for controlling the damper characteristics of semi-active and active shock absorbers [7], a straightforward extension of the previous approaches is the soft sensing of the rear suspension behavior (stroke), which the authors aim to, by exploiting the analytical redundancy between vertical dynamics of the motorcycle suspension system as whole. Indeed, according to the half-car model (which linearly approximates the in-plane dynamics) the rear suspension response to the road disturbances is strongly influenced by the heavy and pitch movements of the front suspension and the motorcycle body respectively as well as by the road profile actually experienced by the front wheel.

The soft sensor for the rear stroke could be useful for multipurpose. First of all, the design of an inferential model intended to reduce the measuring hardware requirements (rear stroke sensor, pair of accelerometer and so on) may result into a significant source of budget saving and increasing system reliability (about the series system, the fault probability is decreasing with the number of the devices operating in the harsh environment).

As second application example, the soft sensor may be adopted to the real-time estimation of the system variable as opposed to the delayed measurement and/or actuation by means of the corresponding hardware devices. More in details, during riding at low-medium longitudinal speed, the prediction of the real suspension dynamics could be exploited by the control unit ([8]-[9]) to compensate for the time response of the semi-active shock absorber (such as the electronically-controlled linear valve or Magneto-Rheological damper [10]).

Finally, the soft sensor of the suspension stroke may be adopted for sensor validation (the particular kind of fault detection, in which the system to be monitored is a sensor or a set of sensor) following the (physical/analytical) redundancy-based approach typically adopted in the automotive safety (for example, the dual pedal sensor exploited for monitoring the driver's torque demand). In such framework, the usefulness of the soft sensor is twofold. First, it can be paralleled with the actual stroke sensor, and faults can be detected by comparison between the outputs of actual and soft sensors. Second, it can be exploited to provide an estimate of the sensor output in the case of sensor fault. Therefore, it can be used as a back-up device till the actual sensor is not replaced during the servicing.

In the present work, the mathematical model allowing to infer the rear suspension stroke on the basis of its dependence

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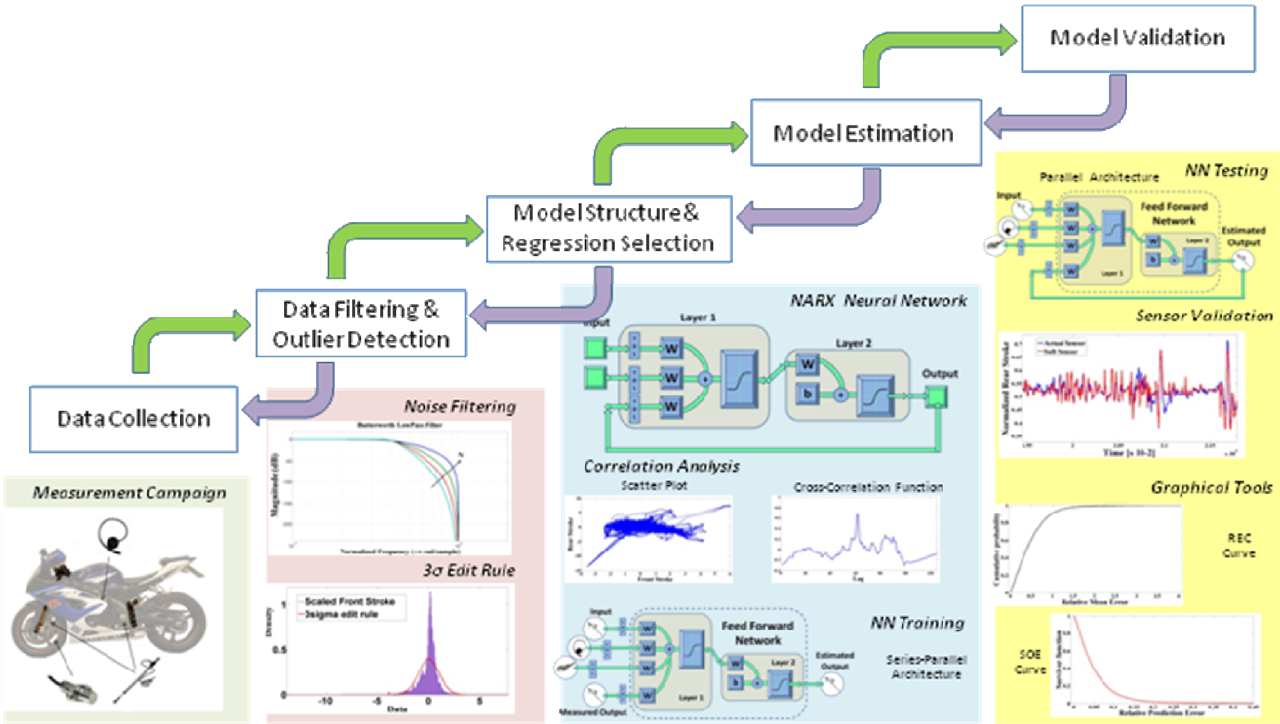

Fig. 1. Data-driven identification of a Soft Sensor: main steps and techniques applied to rear stroke sensor.

on a set of influential variables is developed according to a data-driven approach. Thus, the paper is organized as follows: motivations and details of each step included in the proposed methodology are described in Section II. Experimental results concerning with the application of the method to the sensor validation of the rear stroke for a pilot motorcycle are included in Section III, whereas in Section IV the outcomes from the post-processing analysis are discussed in terms of the main Instrument Fault Detection and Isolation (IFDI) issues [11].

II. METHODS

The typical steps that a softer designer is faced with are reported in the block scheme of Fig.1 as well as the correspondingly adopted techniques. It should be borne in mind that the depicted procedure is a trial and error one, so that if a model fails the validation phase, the designer should critically reconsider all aspects of the adopted design strategy and restart the procedure trying different choices. This can require the designer going back to any of the steps illustrated in Fig.1, and using all available insight until the success of the validation phase indicates that the procedure can stop.

A. Data Collection

The very first step in any model identification is the critical analysis of available data from the process/system of interest in order to select both candidate influential variables and events. According to the data driven approach, the model designer might select data that represent the whole system dynamics by running suitable measurement campaign on the process, which give insight into relevant variables, system order, delays, sampling time, operating range, nonlinearity.

B. Data Filtering

Digital data filtering is typically introduced to remove high frequency noise and offsets. In order to prevent larger magnitude variables to be dominant over smaller ones during the identification process, data scaling should be also performed. Finally, since the presence of outliers (i.e. data inconsistent with the majority of recorded data) can greatly affect the performance of data-driven soft sensor design, suitable identification strategy is required.

C. Model Structure & Regression Selection

Model structure is a set of candidate oriented representations, where a set of dependent variables (i.e. the system outputs) are the consequence of a set of independent variables (i.e. the system inputs). The model structure selection step is strongly influenced by the purpose of the soft sensor design. In particular, when the variable inferred by the soft sensor is the output of a dynamic system, two possible choices are common:

i. to restrict the model structure to linear (MA) or nonlinear (NMA) Moving Average models that do not require past samples of the output variable (this corresponds to focusing on the class of Finite Impulse Response (FIR) structure);

ii. to use of Auto-Regressive with eXogenous inputs (ARX) or Nonlinear ARX (NARX) model structures, which perform finite and small step-ahead prediction of the variable (in this case, the model has among its inputs past samples of its own estimations with corresponding feedback of model errors: auto-regressive structures are generally more efficient than the corresponding MA or NMA structures in the very first predicting steps but, generally, their performance quickly degrades due to error propagation).

Closely connected with the problem of model structure is the Regression selection, i.e. identify the subset of relevant model inputs from the initial set of influential variables previously introduced. The *Correlation Analysis* is often a suitable tool: the estimated normalized cross-correlation function between each candidate independent variable and the system output is typically investigated in terms of the peak magnitude.

D. Model Estimation

It consists in determining a set of parameters which will identify a particular model in the selected class of candidates, on the basis of available data and suitable criteria. Although, approaches such as *Least Mean Square* (*LMS*) based methodologies have been widely used for linear systems, a corresponding set of theoretical results is not available for nonlinear systems, whereas *Artificial Neural Networks* (*ANNs*) and Neuro-Fuzzy systems have become standard tools due to the good performance obtained for a large number of real-world applications. Within the modeling of nonlinear dynamic systems, the use of NARX Network revealed very effective both as predictor (i.e. to estimate the next value of the input signal) and nonlinear filter (when the target output is a noise-free version of the input signal).

More in details, the NARX Network is a recurrent dynamic network, with feedback connections enclosing several layers. The defining equation (Eq. (1)) for the NARX model is:

$$y(t) = f\left(y(t-1),..,y\left(t-n_y\right),u(t-1),..,u(t-n_u)\right)$$

where the next value of the dependent output signal y(t) is regressed on previous values of the output signal and previous values of an independent (exogenous) input signal u(t). You can implement the NARX model by using a Feed-Forward NN to approximate the function *f*.

E. Model Validation

It is the phase required to verify whether the model is able to adequately represent the underlying system. As general rule to be followed, data used for model validation (*Test Set*) should be different from those used for model estimation (*Training Set*). In fact, a model could have satisfactory behavior with the learning data set and work very poorly when processing a new data set. This precaution is useful for investigating over-fitting phenomena. In particular, graphical approaches can be very powerful tools for model validation. The Regression Error Characteristics (REC) and Sliding Occurrence Error (SOE) curves introduced in [12]-[13] to provide both synthetic and detailed indication about the ANNs performance have been considered to compare the proposed architectures.

REC curve plots, for each point (x, y), the relative occurrences of regression function outputs (on the y-axis) that are within a given error range (tolerance) (on the x-axis). The resulting curve estimates the cumulative distribution function (CDF) of the error that may be defined as the relative difference between the ANN prediction and the actual system output. The area over the curve (AOC) is a biased estimate of the expected mean error and provides a measure of the mean accuracy; the closer the curve to the y-axis the better the performance expected for the regression function.

The REC curve gives only integral information disregarding the time distance between regression errors. On the other hand, this knowledge that provides a kind of "local accuracy" could be effectively adopted in the context of the sensor validation. Indeed, within this application (where focus is on the fault detection performance), once a suitable threshold is fixed as the maximum tolerable error, it is preferable to use the ANN able to warrant a small percentage of errors exceeding the threshold in a time interval rather than a ANN that assures the lowest mean error even if characterized by some time windows in which a higher percentage of threshold overcoming occurs.

This feature may be highlighted by the SOE curve: with reference to a moving window constituted by L successive samples, it plots the error tolerance (defined as the maximum relative deviation) on the x-axis and the corresponding relative occurrences in L of the regression error on the y-axis (in other words, the SOE curve represents the survivor function of the error tolerance).

III. EXPERIMENTAL RESULTS

The data driven approach previously described was applied for the soft sensor design and validation of the rear suspension stroke by considering the SUZUKI GSX-1000 model as test motorcycle suitably equipped [14]. Details about the measurement campaign and post-processing analysis are reported in the following.

A. Data Collection

This identification step was performed by taking into account the following riding conditions: a stretch of cobblestone (which excite the suspension response to the pitch); a rough urban road negotiated at low-medium speed (accordingly the motorcycle receives a mixed pitch-have excitation simultaneously, on a broad spectrum), an extra-urban road negotiated at high-medium speed (which mainly introduces pure heavy excitation), a region with multiple speed bumps (in order to highlight the suspension behavior against concentrated obstacles and significant load transfer). About 1 hour of data acquisition (corresponding to 12 records of the test lap) was collected for the following signals: fork stroke, pitch rate, roll rate, longitudinal speed, breaking activation (as independent variables) and rear shock stroke (as dependent variable).

B. Data Filtering

The recorded data came from the sampling process of the analog signals at 1 kHz (that is also the control loop frequency typically adopted for the semi-active suspension control). Data resampling at 100 Hz was proposed to avoid managing huge data sets and reduce data collinearity. The *min-max normalization* method was adopted for data scaling, whereas the detection of outliers was performed according to the *Hampel identifier* (i.e. the 3σ edit rule with a robust scaling) [15]. Namely, to reduce the influence of multiple outliers in estimating the mean and standard deviation of each variable, the mean is replaced with the median and the standard deviation with the median absolute deviation from the median.

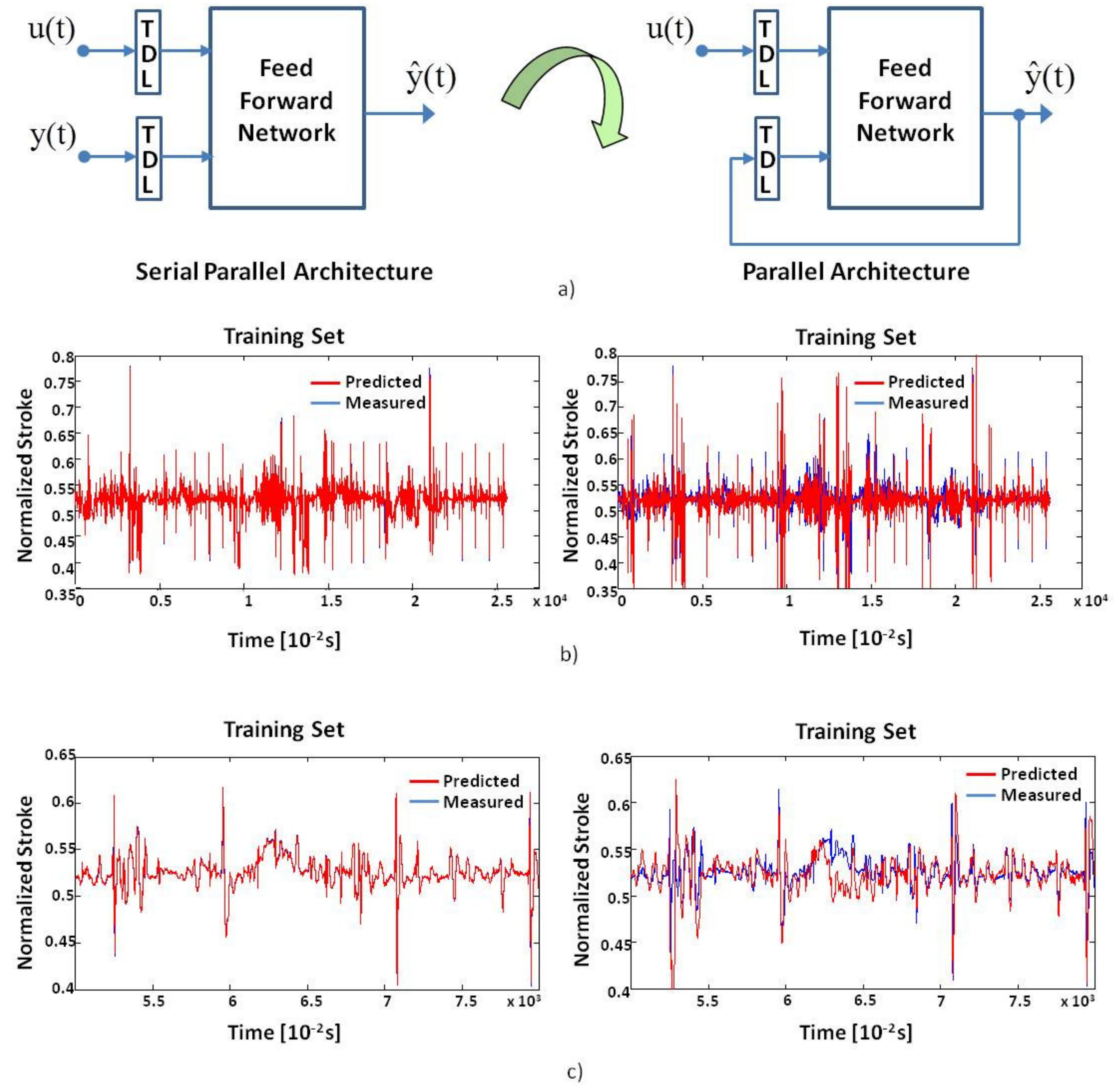

Fig. 2. Training of NARX Networks for the prediction the rear stroke:
a) comparison of the Training schemes: Series-Parallel (open loop) vs. Parallel (closed loops);
b) comparison of the prediction output for the Training Set;
c) magnification of b).

C. Model Structure & Regression Selection

Since the sensor validation was pursued, the approach based on exogenous inputs was preferred. By considering observation intervals strictly close to the system dynamics, it was prevented the model error effects propagate for a large number of successive samples. Moreover, since the half-car model hypotheses that the suspension system works close to a steady state condition and does not account for the steering and linkage nonlinear effects which mainly results in a varying wheel base and transfer load, the *NARX model* appeared as the most straightforward choice. Finally, as result of the performed *Correlation Analysis*, the fork stroke, the pitch rate and the longitudinal speed emerged as the most relevant inputs and further considered in the next design steps.

D. Model Estimation

The soft sensor for the rear suspension stroke was modeled (as function of fork stroke, pitch rate and the longitudinal speed) by adopting the *Neural Network Toolbox* included in MathWorks MATLAB™. More in detail, the Network

Training was performed by taking into account the Series-Parallel scheme, where the true output was used instead of feeding back the estimated output (as schemed in Fig.2.a). This has two advantages. The first is that the input to the feedforward network is more accurate. The second is that Static Back-Propagation can be used for training the resulting network. The model identification was carried out with reference to the number N of neurons in the hidden layer (ranging from 5 to 25), and the tapped delay d (range from 10 ms to 100 ms) resulting in a total of 25 combinations. Moreover, a Training Set including more than 25.000 successive samples (randomly selected from the re-sampled and filtered data) and 100 epochs was considered. An example of NARX Network training is reported in Fig. 2.b-c, where you may note the satisfying matching between the true (measured) and predicted output (suspension stroke range normalized as [0.0 ÷ 1.0]), which has been achieved by converting the Series-Parallel configuration (open loop) to the Parallel configuration (close loop) through the suitable Toolbox functions.

The REC curve was adopted to select the NARX Network (in terms of neurons and delay) which guarantee the best accuracy over the Test Set (about 330.000 samples from the recorded data). The relative regression error E_r is defined according to:

$$E_r = \left|\frac{y_p - y_m}{y_m}\right| \qquad \text{Eq. (2)}$$

where y_p is the normalized rear stroke predicted by the NARX model (at each sampling point) and y_m is the corresponding true output measured by the rear sensor.

As an example, Fig. 3.a reports the REC curves corresponding to the proposed architectures: the NARX model with N=15 and d=10 is able to keep the regression error lower than 10% for over the 95% of the Test Set (as depicted in the magnification of Fig. 3.b).

Moreover, Fig. 4.a shows the SOE curves for different window length L over the Test Set corresponding to the most accurate NARX model. For each sample of the Test Set, the maximum absolute deviation $E_{max,L}$ is defined according to:

$$E_{max,L}(i) = max_k \left|\frac{y_p(i+k) - y_m(i+k)}{y_m(i+k)}\right|_{k=0,1,..,L_S-1} \qquad \text{Eq. (3)}$$

where L_s is the number of samples included in the window length. As highlighted in Fig. 4.b, about the most accurate NARX Network, the maximum prediction error exceeds 10% only for a small quote (16%) of the Test Set when a 100 ms window is considered.

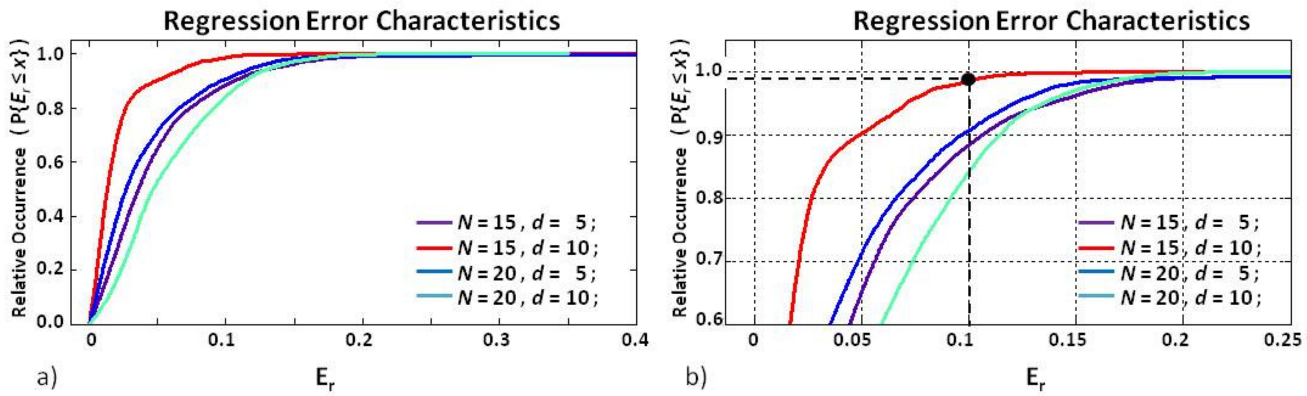

Fig. 3. Graphical tools for Model Validation applied to the rear stroke sensor:
a) REC curves for comparing NARX Neural Network (N, number of hidden nod, d, time delay);
b) Magnification of a).

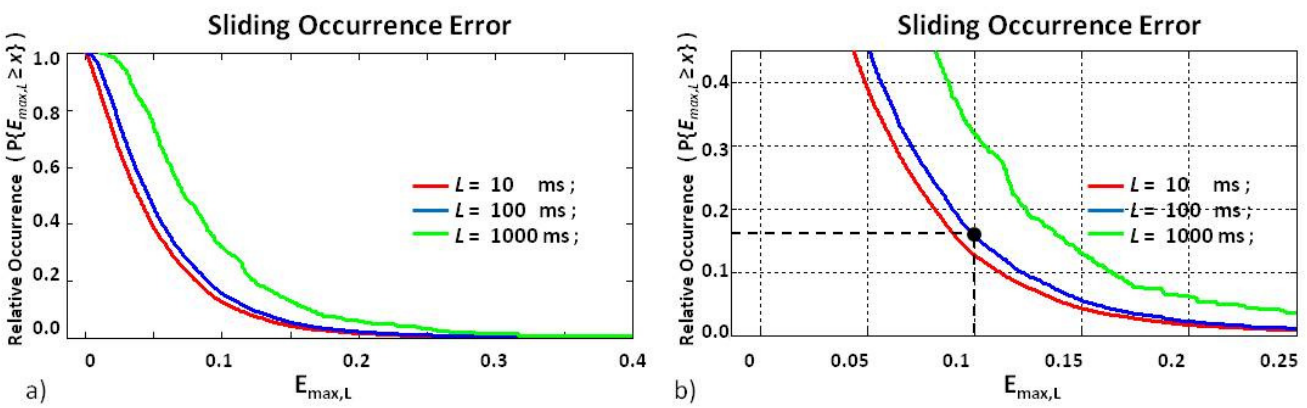

Fig. 4. Graphical tools for Model Validation applied to the rear stroke sensor:
a) SOE curves for NARX Neural Network (N=15, d=10) as the window length is varying;
b) Magnification of a).

IV. CONCLUSIONS

A data driven approach has been introduced for the soft sensor design and validation of the motorcycle vertical dynamics in order to improve road safety in terrestrial transportation. The methodology is mainly focused on both the training of NARX Neural Networks and the graphical tools (namely the Regression Error Characteristics and the Sliding Occurrence Error curves) for the accuracy estimation of the output prediction.

The measurement campaign and post-processing analysis concerning with the suspension stroke sensor have highlighted the validity of the proposed solution in terms of both static and dynamical behavior (represented respectively by the mean error and the sliding maximum deviation in the output prediction). Experimental results lead the authors to adopt the NARX model as a useful benchmark (in terms of false alarms and correct faults) in the development and implementation of IFDI strategies for motorcycle rear stroke sensors.

Thus, further investigations will be addressed to the adoption of SOE results and threshold identification (about maximum deviation and sliding window length) for introducing suitable detection schemes, wherein the residual generation (from comparison between the measured and predicted sensor output) and correlation analysis may be able to on-line detect and isolate small faults (due to discalibration/aging), which typically affect the sensors for vertical dynamics.

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